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A Longitudinal Analysis of Job Skills for Entry-Level Data Analysts

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ABSTRACT

The explosive growth of the data analytics field has continued over the past decade with no signs of slowing down. Given the fast pace of technology changes and the need for IT professionals to constantly keep up with the field, it is important to analyze the job skills and knowledge required in the data analyst and business intelligence (BI) analyst job market. In this research, we examine over 9,000 job postings for entry-level data analytics jobs over five years (2014-2018). Using a text mining approach and a custom text mining dictionary, we identify a preliminary set of analytic competencies sought in practice. Further, the longitudinal data also demonstrates how these key skills have evolved over time. We find that the three biggest trends include proficiency with Python, Tableau, and R. We also find that an increasing number of jobs emphasize data visualization. Some skills, like Microsoft Access, SAP, and Cognos, declined in popularity over the time frame studied. Using the results of the study, universities can make informed curriculum decisions, and instructors can decide what skills to teach based on industry needs. Our custom text mining dictionary can be added to the growing literature and assist other researchers in this space.

Keywords: Business analytics, Business intelligence, Careers, Employment skills, Job skills, Text processing

1. INTRODUCTION

The explosive growth of the data analytics field has continued over the past decade with no signs of slowing down. According to CIO.com, the data analytics field included two of the top five hot and high-paying tech skills in 2018 (Scorsone, 2018). LinkedIn also published the top seven skills in high demand for 2019, and two of these seven skills were in a data analytics-related field (Bila, 2018). IBM predicts that the demand for data analysts will increase by 28% by 2020 (Columbus, 2017).

Besides the fact that the number of jobs greatly outpaces the number of qualified candidates, there are other concerns in the field. One of the major concerns is defining what exactly data analysts do. The data analyst and business intelligence (BI) analyst fields vary greatly, and professionals have a hard time understanding the skills needed. In one study, Bowne-Anderson (2018) spoke to over 30 data analysts and BI analysts across a wide array of industries and academic disciplines to find out what their jobs entail. One highlight of the interview suggests that the ability to communicate the results of analytics is more important than the ability to use sophisticated deep learning models. Other results suggest that specialization is becoming more important and that data ethics need to come from within data science itself as well as from legislation, grassroots movements, and other stakeholders.

Given the fast pace of technological changes and the need for IT professionals to constantly keep up with the field, it is important to analyze the job skills and knowledge required in the data analyst and BI analyst job market. Because the field changes so rapidly, it is also just as important to understand what data analyst and BI analyst skills are trending upward as well as trending downward over time. Currently, only a few studies (Deng, Li, and Galliers, 2016; Luo, 2016) have attempted to address these concerns and have not fully explored the changing trends. To address this gap, we seek to answer the following questions:

1. What data analyst job skills and knowledge remained steady from 2014-2018?
2. What data analyst job skills were popular in the past, but are less attractive now?

3. What data analyst job skills are gaining attention in the current job market?

This study focuses on the job postings for entry-level hires into the fields of data analyst and BI analyst. We define *entry-level hires* as individuals who are completing their undergraduate degree and wish to start a career in data and/or BI analytics. Entry-level hires could also include individuals who have an undergraduate degree in a field other than business, math, or computer science or individuals who are working in a non-analyst field and looking to change careers to pursue a career in data and/or BI analytics. According to GlassDoor, the data analyst job is one of the nine perfect jobs for career changers (Moore, 2018). Our study explores the job skills and knowledge for data analyst and BI analyst jobs on a large scale. Using text analysis, we analyze approximately 9,000 entry-level job postings from Indeed.com in the data analyst and BI analyst field from 2014 to 2018.

The results of this study have several practical contributions. First, as undergraduates start to define their career aspirations in their last years of college, these findings can help focus their skills. Students can start choosing electives that strengthen certain skills that are in hot demand in the current data and BI analyst job market. Second, the results of this research can also assist those individuals who want to change their current career to an entry-level data or BI analyst role. Those individuals can start pursuing professional training, university certificates, or online courses that can teach the skills that are in hot demand in this market. Third, these findings can help undergraduate programs and professional training companies focus their course offerings to align with the latest skills in this rapidly changing job market. Lastly, the results of this research can help companies retool and train their employees on the latest data and BI analyst skill sets to stay competitive in a data-driven business ecosystem.

2. LITERATURE REVIEW

2.1 Data Science, Data Analytics, and Business Intelligence

The concepts of data science, data analytics, and business intelligence are not new. One of the founding disciplines, statistics, has been around since the mid-1700s. Mathematicians have been building models for centuries, and even basic database concepts have been around since the 1960s. Companies have been analyzing data to improve consumer interaction, make production more efficient, and reduce cost since the middle of the 20th century (Mills, Chudoba, and Olsen, 2016). However, there has been explosive growth in these fields over the past decade. Mills, Chudoba, and Olsen (2016) have attributed this growth to three trends. The first trend is enhanced technology infrastructure that can handle terabytes of data in real time (Silva et al., 2014). The second trend is the advancement of data storage and transformation. The third trend is the expansion of analytical tools and techniques (Chen, Chiang, and Storey, 2012; Davenport, Barth, and Bean, 2012). These three trends have allowed the field to expand from its established foundations.

The terms *data science, data analytics, business intelligence, and big data* are used throughout the literature, but it is helpful to define these terms. *Data science* is a field that finds value in data and uses this value to create additional data products (Loukides, 2011). Davenport and Patil (2012) define a data scientist as a combination of a data hacker, analyst, communicator, and trusted adviser.

Data analytics refers to the process of inspecting, cleaning, transforming, and modeling data with the goal of supporting decision-making (Lewis-Beck, 1995). *Business analytics* is a subfield of data analytics that refers to problem recognition and problem solving that happens within the context of business situations (Holsapple, Lee-Post, and Pakath, 2014). In one study, Turel and Kapoor (2016) examined the gap between business school curricula and presumed industry needs in business analytics. They identified business analytics courses as those that cover topics such as "business intelligence, data visualization, big data, and their roles in business strategy and in improving business performance" (p. 99).

The Gartner Group introduced the term *business intelligence* in 1989, describing a set of concepts and methods to improve business decision making by using fact-based support systems (Power, 2007). Expanding on this definition, business intelligence is a broad category of applications, technologies, architectures, and processes for gathering, storing, accessing, and analyzing operational data to provide business users with timely competitive information to enable better insights for operational and strategic decision making (Gupta, Goul, and Dinter, 2015).

The term *big data* is more than just a large amount of data; it also includes the tools and procedures used to manipulate and analyze the data (Burkholder, 1992). Big data is driving changes in what types of data are being collected, how often data are collected, and how much data are being collected (Gardiner et al., 2018). Big data also has the ability to analyze varied datasets with respect to variety (structured and unstructured data), volume (amount of data), and velocity (archival versus streaming data).

To help clarify the distinction between the terms data science and data analytics, Aasheim et al. (2015) examined a small sample of undergraduate programs in the U.S. Some programs called themselves data science programs and some called themselves data analytics programs. They found that there are similarities between the two differently named programs. These similarities include an increase in the number of courses on statistics, data management, data mining, data visualization, and other modeling techniques. They also found several differences between the programs. Mainly, data science programs were interdisciplinary in nature and required additional math (at least through linear algebra), programming, and statistics courses, whereas analytics programs covered data warehousing and were mainly located in the business school. These data science characteristics align with the definition of data science as defined above by Loukides (2011) and Davenport and Patil (2012).

As far as the current job market, according to a report from Burning Glass Technologies, Business-Higher Education Forum, and IBM, the fields of data-driven decision makers, functional analysts, data analysts, and analytical managers all had double-digit projected job growth over the next five years (Miller and Hughes, 2017). Another report by PWC estimated that by 2021, only 23% of educators stated that graduates would have BI&A skills, while 69% of the employers prefer job candidates with those skillsets (PWC, 2017).

2.2 Skills, Knowledge, and Abilities

Since we are analyzing each job posting in its entirety, there are several different categories to examine. These categories include skills, knowledge, and abilities. *Skills* are competencies developed through training or experience, *knowledge* is the theoretical or practical understanding of a subject, and *abilities* are the talents involved in being able to do something (Lauby, 2013).

There are two similar studies that investigate the business analytics job market. In one of the studies, Deng, Li, and Galliers (2016) investigated the skills, knowledge, and abilities that employers required for a business analytics role. In addition, they analyzed the job postings by business degree versus non-business degrees (i.e., computing, engineering, statistics, or mathematics). Using Latent Semantic Analysis, Deng, Li, and Galliers analyzed 71 unique job postings from LinkedIn. They discovered that the postings were split fairly evenly between business and non-business degrees and that the top two industries looking for employees were healthcare and information technology services. In addition to their findings, the researchers mapped the required skills to Bloom's taxonomy (Bloom, 1956) to help institutions align course design with student learning objectives.

The other similar study analyzed 1,216 job advertisements from Indeed.com that contained the word "big data" in the job title (Gardiner et al., 2018). Using the pile-sort methodology, they found two major insights. The first insight was that a number of job postings emphasized the design and development of analytical systems. The second insight was that soft skills still remain very important in job postings, even given the demand for skills in new and emerging technologies. In addition to these insights, the authors created a Big Data Discipline Skills Conceptual Model. This model highlights and provides insight into the complexity of the big data discipline.

It is worth noting that we found it difficult to differentiate between skills and abilities. Given the definition that skills are competencies and abilities are talents, it is hard to determine the difference with static job postings. For example, is a job posting asking for an applicant to generate data mappings a skill or an ability? For our purposes, the category does not matter, as it is mandated by the employer. Therefore, we followed Gardiner et al. (2018) in combining the terms skills and abilities into one term, which we will refer to as skills. We further break down skills into two groups. The first group is higher-level general domain skills (e.g., business intelligence and statistics), and the second group is specific software skills (e.g., SAP and R). We refer to knowledge as the academic background needed for the job posting (i.e., high school, bachelor's degree, master's degree, or doctoral degree).

2.3 Prior Relevant Studies

Another study closely related to our research is a study of the requirements needed for entry-level analytics professionals. Luo (2016) examined job ads posted on three major sites (LinkedIn, Monster.com, and Indeed.com) over a six-month period. After analyzing 924 job postings, the author concluded that companies expected entry-level professionals to be able to work in teams and work with databases and spreadsheets. The study also found that data mining, optimization, and other advanced analytical methods were rarely listed in postings for entry-level positions.

A related study took a broader approach by examining trends in required job skills for IT professionals from 1988 to 2003 (Gallivan, Truex, and Kvasny, 2004). The researchers performed content analysis on 17 years of samples from the job ads section of *Computerworld* and the Sunday classified job ads section of a major metropolitan newspaper. Their goals were to 1) determine the most dramatic trends for IT positions, 2) determine the most dramatic trends for required skills, and 3) prove the forecasts offered by researchers in earlier studies were accurate. They found that most of their results were consistent with previous forecasts. For example, employers were asking for an ever-increasing number and variety of skill sets from new hires, and programming and software development skills remained important. They also discovered that although employers emphasized the need for well-rounded individuals and strong soft skills, the job postings prioritized hard skills.

Using a web content data mining application, one study (Aken et al., 2010) examined approximately a quarter-million unique IT job descriptions. Using cluster analysis, they condensed job postings from various job search engines into 20 different job skill clusters. At the time of publication, the top five job skill clusters were IT managers, security specialists, project analysts/managers, system administrators, and database developers. Aasheim et al., (2012) presented an extension to two previous studies (Aasheim, Li, and Williams, 2009; Aasheim, Williams, and Butler, 2009) in which they examined knowledge and skill requirements for entry-level IT employees. Using a survey and a basic z-test, they discovered that the top skills needed by employers were personal and interpersonal skills, with honesty and integrity ranked most highly.

Text analyses of job postings have been performed in other business- and information-related fields. In the field of information science, one research project examined job descriptions and advertisements for three data curation-focused positions (Lyon et al., 2015). Their goals were to 1) discover what skills were required for data science roles, 2) map data science roles to current curriculum topics and course offerings, and 3) develop new collaborations and partnerships in the data science curriculum. Using job postings from Indeed.com from January 2014 to April 2015, the researchers examined postings in the fields of data librarian, data curator, and data archivist. Among other findings, the research demonstrated that employers were seeking data-savvy graduates who were work-ready.

Another study in the field of marketing used content analysis to examine 500 marketing job postings ranging from entry-level all the way to senior-level positions (Schlee and Harich, 2010). Not surprisingly, they found that there were considerable differences in the skills and knowledge required for all different levels of marketing jobs. They also discovered that technical skills appeared to be much more important than what had been documented in earlier marketing research.

In summary, there are several studies that examine the data analytics job market. Our study differs from these previous studies in several ways. First, we examine a longer time frame (i.e., five years) compared to only several months (e.g., Luo, 2016; Gardiner et al., 2018). We also analyze about 9,000 job postings compared to other studies that only analyzed about 1,000 job postings (e.g., Luo, 2016; Gardiner et al., 2018). Lastly, we use several terms to search for job postings compared to a specific search term like "big data" (Gardiner et al., 2018), "BA positions" (Deng, Li, and Galliers, 2016), or "data analyst" (Luo, 2016).

3. METHODOLOGY

In this study, we use a text mining approach to systematically analyze job postings to identify the skills and knowledge expected for entry-level data analyst positions. We follow the established protocols in previous IS research (Mudambi and Schuff, 2010; Wang, Kannan, and Ulmer, 2013) for data collection and text mining analysis. Figure 1 provides an overview of the data collection, processing, and major analyses for this study.

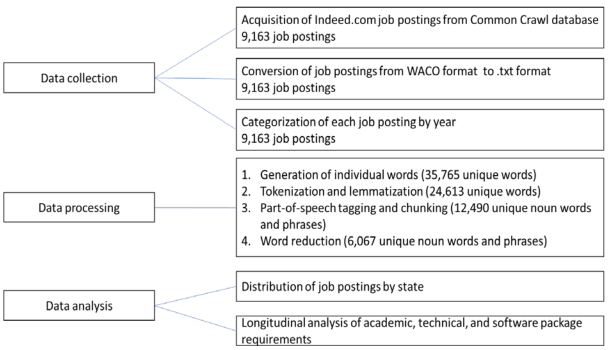

Figure 1. Data Collection, Processing, and Analysis

3.1. Data Collection

3.1.1 Data source. We started by examining job postings on Monster.com, Indeed.com, and LinkedIn.com. We discovered that all three job posting sites shared mostly the same job postings. Therefore, we decided to focus our search on just one of the job posting websites to avoid duplication. In 2010, Indeed.com passed Monster.com to become the highest-traffic job website in the United States. Currently, Indeed.com boasts that they have over 3 million companies with 250 million job seekers (http://www.Indeed.com).

Our first challenge was how to collect job postings over past years because job websites do not keep historical data for more than one year. Therefore, we used the Common Crawl dataset to address this problem (http://commoncrawl.org/). Common Crawl is a non-profit organization that builds and maintains an open repository of web crawl data that is, in essence, a copy of the Internet. Common Crawl data contains over 25 billion web pages (Batikas, Claussen, and Peukert, 2018) and is widely used in hundreds of research projects (Batikas, Claussen, and Peukert, 2018; Cafarella et al., 2018). Since we were only interested in the content from Indeed.com, we only examined a very small fraction of the Common Crawl corpus.

3.1.2 Search terms. A key component of any text analysis is to first define the search terms to be used. We examined previous studies (Sodhi and Son, 2009; Liberatore and Luo, 2013; Deng, Li, and Galliers, 2016; Luo, 2016) to determine key search terms. We used a wildcard search of *business analy*, data analy*, and business int**. These wildcard searches returned the following results: data analyst, data analytics associate, data analysis, business intelligence analyst, and business analytics.

The scope of this research is examining entry-level positions. During our initial search process, we used the search term "data scientist" (technically, we used a wildcard search of data sc*). After examining a random sample of the job postings returned, we discovered that these job postings required at minimum a bachelor's degree plus at least a few years of work experience in the data analytics field. We considered these not to be entry-level positions and out of the scope of our research. Therefore, we excluded the terms data scientist, data science associate, and data science analyst from our search terms. The total number of job postings downloaded from Common Crawl for each year from 2014 through 2018 that fit our search criteria is listed in Table 1.

Year	Number of Job Postings
2014	1722
2015	1955
2016	1735
2017	1888
2018	1863

Table 1. Number of Job Postings by Year

3.2. Data Processing

In order to accurately and automatically acquire job skill content from large-scale texts, natural language processing (NLP) techniques must be introduced (Jurafsky and Martin, 2008). According to research in computational linguistics (Church, 1988) and our observations of the words describing job skills in the job postings, the main job skill information comes from nouns. Therefore, verbs, adjectives, and prepositions could be safely removed without losing the main information. We applied part-of-speech tagging to filter the nouns for further analysis.

The data processing can be broken down into the following steps:

1. Convert 9,163 job postings to individual words. These job postings have a total of 4,499,672 words and 35,765 unique words.
2. Normalize/tokenize words. By applying lemmatization, total words and unique words are reduced to 2,867,392 and 24,613, respectively.
3. Apply part-of-speech (POS) tagging and chunking. There are 12,490 unique noun words and phrases remaining.
4. Remove rare or common nouns and noun phrases. Any nouns and noun phrases that appear in fewer than 1% or more than 75% of the job postings are removed. The number of unique noun words and phrases is further reduced to 6,067. With 6,067 unique nouns and noun phrases left, it is feasible for us to manually analyze the key words that are relevant to data analyst job skills.

3.2.1 Part-of-speech tagging (POS). Part-of-speech tagging is a process of assigning morphological tags or categories (classes) to each token (Voutilainen, 2003). Commonly, in the context of NLP, a token is preferred, rather than a word, because each token has a unique meaning. After POS tagging is applied, the tokens in a sentence are marked into proper classes. In this research, the Stanford Log-linear Part-Of-Speech Tagger, which was developed by the NLP group at Stanford University, has been adopted. The Stanford Log-linear Part-Of-Speech Tagger is considered the most widely used POS tagger, as this tagging system can achieve more than 95% accuracy in English tagging (Toutanova and Manning, 2000).

3.2.2 Chunking. It is not uncommon that single noun tokens can fail to represent some job skills, such as interpersonal skills (adj + noun) or Microsoft Office (noun + noun). In NLP, these short phrases are identified as noun phrases (NP). It is more appropriate to consider these NPs combined as a noun token, rather than separate tokens. Chunking addresses these issues. Chunking is a process of extracting phrases from text data. Therefore, in addition to using part-of-speech tagging, chunking is also applied to extract NP. Tokens that follow the grammatical patterns described below are extracted for further analysis:

1. noun, for example, Python, R, Excel, Tableau
2. noun + noun, for example, Microsoft Office, management software, data visualization
3. gerund + noun, for example, programming skills, writing skills
4. adjective + noun, for example, interpersonal skills, analytic capability

3.2.3 Dictionary development. A key step in text mining involves creating or using an existing dictionary of relevant words in order to categorize and classify the search results. Because there is sparse research in this area and the field is constantly evolving, we did not have an exhaustive dictionary to reference. Therefore, we built our own dictionary. There are two ways to build a dictionary from scratch – a theoretical approach and an empirical approach (Luo, 2016).

The theoretical approach involves using existing terms in relevant literature. We started by examining literature that has used a text mining approach to identify job skills in business analytics (Deng, Li, and Galliers, 2016) and operational research skills (Sodhi and Son, 2009). Starting with a list of 367 words, two expert coders in the field of data analytics agreed on a final list of 149 words that are relevant to the data analytics field. We started our dictionary with these 149 words. The Kappa interrater reliability was 0.984, which is above the well-established mark of .70 according to Landis and Koch (1977) and Bowers and Courtright (1984). Coding disagreements were discussed, and eventually a consensus was reached.

Although these 149 words were a good starting point, at first glance they did not fully reflect the current job market of the data analytics field. For example, the programming language Python was not included in the original list although it is a very popular programming language in the field. Therefore, we used an empirical approach to update our dictionary. An empirical approach involves deriving words from a large sample of representative job ads (Sodhi and Son, 2009). Using the original corpus of job postings from Indeed.com, we identified 6,067 single words. A vast majority of these words were not relevant since they included every word in a job posting. For example, the words "position," "user," and "education" were not useful in our dictionary. The same two coders agreed on a final list of 40 words to add to the dictionary. New additions to the dictionary included words like "Python," "R," and "Pentaho," which are all relevant to the data analytics field. The Kappa interrater reliability was 0.956, new coding disagreements were discussed, and a consensus was reached. Finally, similar concepts were merged and grouped into three primary categories: general domain skills, software skills, and knowledge. This process led to a dictionary containing three primary categories with 14 sub-categories and 186 keywords and phrases. The final dictionary is reported in Appendix A.

3.3 Statistical Analyses

In order to answer our research questions to determine if there were significant differences in the skillsets between 2014 and 2018, we tested the difference between two population proportions. The test statistic for measuring the difference between two population proportions is:

$$Z = \frac{(\hat{p}_1 - \hat{p}_2) - 0}{\sqrt{\hat{p}(1-\hat{p})\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

where,

$$\hat{p} = \frac{Y_1 + Y_2}{n_1 + n_2}$$

Longitudinal studies normally use some type of regression. In our case, we did not have any variance within the year; consequently, we could not get a standard error. Therefore, regression would not work with our dataset. We also explored a non-parametric test (i.e., MannKendall) to analyze the trend each year. The MannKendall test examines the trend year over year to determine if the trend is significant over the time period. However, the minimum number of recommended measurements for the MannKendall is at least 8-10 data points (Khambhammettu, 2005). In our case, we only had five years of data, resulting in only five measurements per job skill item. This would result in inaccurate or biased results using a MannKendall test. Therefore, the proportion test was the most appropriate analytical method for our dataset.

4. RESULTS

This section displays the results of our analysis. Due to the large number of keywords analyzed, only significant trends and the most popular general domain skills, software skills, and knowledge areas are displayed in this section. All results (including non-statistically significant trends or less popular skills and knowledge) are reported in Appendix B.

4.1 Analysis by U.S. State

First, we analyzed the results by U.S. state. The top five states in 2018 with the highest number of data analyst jobs, in order, were Virginia, Texas, California, New York, and Illinois. This is not surprising given that three of the top five states in this list are the largest states by population. Because the largest states by population would have the largest number of job postings, we standardized by dividing the total number of job postings by the number of businesses in that state. We collected the number of businesses in each state using the NAICS Association website (NAICS, 2019). The top five states with the standardized job postings, in order, were District of Columbia (not a U.S. state), Virginia, Vermont, Delaware, and Massachusetts. Figure 2 illustrates a heat map for the number of standardized data analytics jobs in 2018.

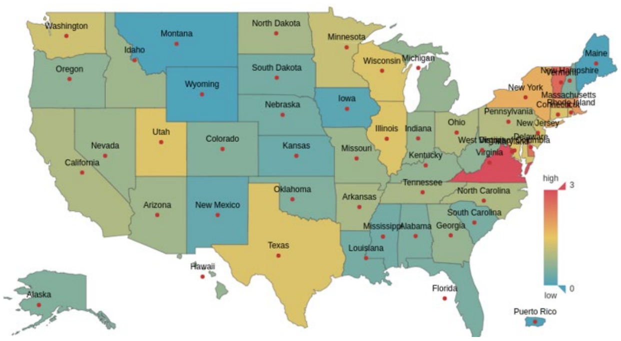

Figure 2. Average Job Postings by State

Table 2 displays the percentage of job postings (job postings in that state/job postings in the U.S.) by state for only states that have a significant difference between 2014 and 2018.

States	2014	2015	2016	2017	2018
Virginia	9.36%	7.92%	11.92%	13.80%	18.00%***
Texas	7.02%	9.06%	8.16%	6.48%	10.20%***
New York	6.30%	7.44%	6.08%	5.10%	9.00%**
Massachusetts	2.52%	3.90%	4.48%	3.36%	4.08%**
Ohio	3.96%	3.30%	2.00%	2.58%	2.76%*
Washington	4.23%	2.34%	2.88%	2.40%	2.40%**
Maryland	3.24%	2.58%	3.84%	2.58%	2.28%*
Georgia	3.87%	3.78%	3.12%	1.80%	2.04%***

Table 2. Distribution of Data Analyst Job by U.S. State
*p < 0.05, **p < 0.01, ***p < 0.001

4.2 Evolution of Knowledge Required
Table 3 displays the percentages of job postings that required bachelor's, master's, MBA, or Ph.D. degrees. Other kinds of academic degrees (e.g., associate degree and high school diploma) are not reported, as the percentages are below 1%, which means few jobs required less than a bachelor's degree

4.3 Evolution of General Domain Skills
Table 4 displays the percentages of job postings that required general domain skills by year.

Knowledge Required	2014	2015	2016	2017	2018
Bachelor	60.60%	60.70%	62.30%	64.80%	70.30%***
Master	12.90%	12.10%	14.30%	15.90%	15.30%*
MBA	6.00%	4.10%	4.10%	5.00%	4.60%*
Ph.D.	3.70%	3.80%	4.40%	4.40%	5.60%**

Table 3. Evolution of Academic Requirements for Data Analysts
*p < 0.05, **p < 0.01, ***p < 0.001

Categories	2014	2015	2016	2017	2018
General Analytics	69.30%	69.70%	69.00%	71.60%	69.90%
General Statistics	22.30%	19.80%	23.00%	29.10%	28.20%***
Modeling	17.20%	15.90%	17.90%	20.30%	21.00%**
Model Development	21.30%	21.10%	22.80%	24.70%	25.70%***
Data Management	40.00%	41.20%	44.50%	50.30%	49.80%***

Table 4. Evolution of General Domain Skills for Data Analysts
*p < 0.05, **p < 0.01, ***p < 0.001

Software Skills	2014	2015	2016	2017	2018
Database System	48.00%	48.80%	52.40%	58.10%	58.90%***
SQL Server	10.40%	12.10%	13.40%	15.20%	17.80%***
Oracle	15.00%	14.00%	13.40%	14.40%	15.50%
Microsoft Access	13.60%	11.60%	11.30%	11.60%	10.40%**
NoSQL	0.70%	1.00%	1.60%	1.50%	1.60%**
DBMS	0.30%	0.60%	0.60%	0.90%	0.90%*
Personal Productivity	30.70%	29.70%	32.60%	32.10%	28.60%
Microsoft Office	18.40%	16.30%	20.60%	18.50%	17.20%
Microsoft PowerPoint	12.10%	13.70%	13.70%	14.20%	13.90%
Business Intelligence	11.30%	12.60%	17.60%	21.80%	23.20%***
Tableau	5.30%	8.30%	13.20%	18.20%	18.90%***
Cognos	7.50%	5.30%	5.30%	5.80%	6.00%*
Power BI	0.10%	0.10%	1.00%	1.60%	1.90%***
Programming Language	16.00%	16.40%	20.20%	21.90%	22.50%***
Python	2.30%	3.30%	6.60%	9.10%	10.70%***
Pig	0.30%	0.50%	0.70%	0.60%	1.00%**
Enterprise System	16.00%	15.80%	16.20%	18.50%	20.30%***
SAP	10.40%	9.00%	8.00%	8.40%	8.30%*
Hadoop	2.00%	2.40%	4.00%	4.50%	5.10%***
Salesforce	3.40%	4.50%	2.80%	4.50%	4.90%*
Azure	0.20%	0.00%	0.80%	1.30%	3.60%***
Hive	0.70%	1.10%	1.80%	1.80%	2.10%***
Google Analytics	0.50%	0.50%	1.50%	1.00%	1.20%*
Statistical Package	10.10%	9.50%	12.40%	15.40%	16.10%***
R	4.50%	4.40%	7.00%	9.60%	11.80%***
SAS	6.60%	6.60%	8.00%	8.80%	9.70%***
SPSS	1.60%	1.90%	2.40%	3.70%	2.50%*

Table 5. Evolution of Software Skills for Data Analysts

*p < 0.05, **p < 0.01, ***p < 0.001

Categories are underlined; subcategories are indented. **Bold** (*italicized)* text indicates a positive (negative) trend between 2014 and 2018.

4.4 Evolution of Software Skills

Table 5 displays the percentages of job postings that required software skills by year. The software skills are sorted by the most popular software skills in 2018 within each category. Only significant trends (i.e., those software skills that significantly increased or decreased from 2014 to 2018) or software that appeared in at least 10% of the job postings are displayed in Table 5. Categories are underlined and subcategories are indented. **Bolded** (*italicized)* software skills indicate a significant increase (decrease) between 2014 and 2018. All results are presented in Appendix B.

5. DISCUSSION

5.1 Discussion by Research Question

We will discuss the results in terms of the research questions. Although the U.S. state analysis was not a research question, it is important to know how data analyst jobs are distributed by U.S. state. According to Table 2, Virginia increased from 9.36% of U.S. job postings in 2014 to 18% of U.S. job postings in 2018. Virginia is the leading data center market in the U.S. and has the 3rd-highest concentration of high-tech workers in the nation. Virginia is "preparing for future growth for IT companies through its top-ranked higher education system to build a pipeline of technology talent" (Key Industries, n.d.). The number of job postings in Texas increased gradually each year as well. Several data centers were established in Texas recently, such as Microsoft and RackSpace. These data centers are developing rapidly, contributing to the increasing job demand in Texas (Mosbrucker, 2018). It is also interesting to note that several states showed declining percentages of job postings from 2014 to 2018. For example, Ohio, Washington, Maryland, and Georgia all show statistically significant decline over time, although not a large number in magnitude.

The first research question is, "What data analyst job skills and knowledge have remained steady from 2014 to 2018?" According to Table 4, general statistics has remained a steady and highly desired skill over the time period studied. In terms of software skills (see Table 5), Personal Productivity Software (e.g., Visio, JIRA), Microsoft Office (not including Access), and Oracle have remained steady and highly desired during the time frame of the study. Other software or languages that has remained steady, although not appearing in a large percentage of job postings, include XML, Teradata, DB2, MySQL, Linux, Visual Basic, and HTML. These general domain skills and software skills have been steady for the past several years and have been documented in other studies (e.g., Gallivan, Truex, and Kvasny, 2004; Luo, 2016).

The second research question is, "What data analyst job skills were popular in the past, but are less attractive now?" None of the general domain skills (see Table 4) showed any decline from 2014-2018. In terms of software skills (see Table 5), only Microsoft Access ($p < 0.01$), Cognos ($p < 0.05$), and SAP ($p < 0.05$) showed statistically significant decline. In terms of Microsoft Access, this may be due to direct competition from other growing, open-source database software like MySQL. There is some anecdotal evidence that Microsoft Access customer support threads have been declining (Microsoft, 2017). Cognos is an IBM business intelligence suite that provides a toolset for reporting, analytics, scorecarding, and monitoring of events and metrics. Although showing decline, the suite is still solid at 6.00% of job postings in 2018. SAP is an enterprise-wide software that helps manage operations and customers. SAP also has BI software including the BI suite, SAP Lumira, Hana, and Crystal Reports. Again, although SAP has shown a statistically significant decrease from 2014 to 2018, it is still a sought-after software skill at 8.3% of job postings in 2018. In summary, three software skills showed statistically significant decline, but these three software packages are still desired skills in the market.

The third research question is, "What data analyst job skills are gaining attention in the current job market?" There are numerous upward-trending general domain skills and software skills over 2014-2018. First, we will examine the upward-trending skills that are in the top 25% of all job postings. The percentages indicate the number of job postings requiring that skill in 2018. General statistics (28%, $p < 0.001$), modeling (21%, $p < 0.01$), model development (26%, $p < 0.001$), data management (50%, $p < 0.001$), database systems (59%, $p < 0.001$), BI (23%, $p < 0.001$), programming languages (23%, $p < 0.001$), and enterprise systems (21%, $p < 0.001$) all increased significantly from 2014 to 2018 and are highly desired skills. In terms of software skills or languages, SQL server (18%, $p < 0.001$), Tableau (19%, $p < 0.001$), statistical packages (16%, $p < 0.001$), SAS (10%, $p < 0.001$), R (12%, $p < 0.001$), and Python (11%, $p < 0.001$) are all in the top quartile in terms of job postings and show a statistically significant increase.

The next set of general domain skills and software packages are increasing in demand over time but represent the next quartile (top 50% of job postings). These software packages include SPSS (3%, $p < 0.05$), Hive (2%, $p < 0.001$), Salesforce (5%, $p < 0.05$), Hadoop (5%, $p < 0.001$), and Microsoft Azure (4%, $p < 0.001$). Although demand for these skills grew during this time frame, they do not represent the top quartile in terms of the number of entry-level job postings asking for that skillset.

Lastly, the skills that grew between 2014 and 2018 but represent the lower 50% of the total entry-level job postings include NoSQL (1.6%, $p < 0.01$), Microsoft Power BI (1.9%, $p < 0.001$), Apache Pig (1%, $p < 0.01$), and Google Analytics (1.2%, $p < 0.05$). An interesting observation is the lack of job postings that mention NoSQL. NoSQL is a non-relational database that is scaled horizontally and means "not only SQL." Only a small fraction of job postings mentioned NoSQL, which indicates that NoSQL has not increased in popularity as previously predicted (Pal, 2016). This is useful information for instructors of database courses. If time is limited, instructors should focus on relational databases instead of NoSQL since it is not highly demanded in the industry.

There are several other software packages that are not trending up or down (i.e, remained steady from 2014-2018) but only represent a very small fraction of entry-level job postings. For example, MongoDB (0.3%), Apache HBase (0.6%), Apache Cassandra (0.2%), Pentaho (0.3%), JavaScript visualization library – D3 (0.2%), STATA (0.5%), Ruby (0.3%), and IBM Watson (0.2%) only appear in a small fraction of job postings. Some of these software programs are taught in database, analytics, and BI courses and are widely known in the industry. However, the results of this research demonstrate that they are not a widely needed skillset for entry-level data analytics jobs. Therefore, given the time constraints of a course, instructors can leave these software packages out of the lesson plan.

Lastly, the top three software and languages that grew the fastest and are mentioned in at least 5% of the job postings in 2018, in order, include Python (11%), Tableau (19%), and R (12%). These are widely used software and languages in industry and are taught across the world in statistics, computer science, and business intelligence courses. As of 2019, these are highly sought-after skills and should remain part of the curriculum in training programs and universities.

Other observations from the analysis include:

1. An increasing number of jobs require candidates to have some programming skills, such as Python and R.
2. An increasing number of jobs emphasize data visualization, which requires proficiency with software like Tableau.
3. A large number of jobs require at least a bachelor's degree (70%).

For data analysts, being familiar with interpreted programming languages like Python and R is a prerequisite, as programming is an inherent part of data processing. Data visualization is the graphical representation of information and data. By using visual elements like charts, graphs, and maps, data visualization tools provide an accessible way to see and understand trends, outliers, and patterns in data.

5.2 Contribution

This research provides a practical contribution for several different audiences. First, universities can use these results to help inform curriculum decisions. For example, the increasing need for programming languages, data visualization, and database skills is imperative. Second, instructors in an analytics course can use these results to decide what technical and software skills should be taught. As mentioned before, if time is constrained, instructors could drop tools like Pentaho and MongoDB. Third, this research is useful for companies that provide business technology training. These training centers can retool their offerings to match industry trends in skillsets and software skills. Lastly, this research can help individuals who are looking to change careers to data analytics. By understanding the trending general domain skills and software skills, individuals can start learning the most desired skills in order to transition careers.

This research also provides some theoretical contributions. First, as part of this research, we built a data dictionary that other researchers and practitioners can use in the data analytics text mining arena. We started with an established dictionary from Deng, Li, and Galliers (2016) and Sodhi and Son (2009). We then used an empirical approach to identify words from job postings that were missing from the original list. This comprehensive dictionary (see Appendix A) was built and utilized for this research. Second, this research can help build the literature in this area. To our knowledge, there are only a few previously published articles that examine the data analytics field using job postings. Our research has a larger corpus and is more current.

5.3 Limitations

There are limitations to this research which should be noted. First, the number of job postings listed is not comprehensive. The job postings only include a sample of all the job postings for that year. This is a limitation of the Common Crawl source. As previously mentioned, Indeed.com does not store historical data, so we used Common Crawl to retrieve the data from years past. There could have been days when Common Crawl did not archive the Indeed.com website, and during that time, a job posting might have appeared and then disappeared. We can make assertions about only a sample of job postings, not the entire corpus of job postings.

Our second limitation is our statistical method to measure trends over time. Since there is only one data point per year, we could not calculate a variance or standard error. This prevented us from using a longitudinal analysis using the five years as a trend. Therefore, our trend analysis only covered two points in time – 2014 and 2018. We did not capture a trend if a skill had the same percentage in 2014 and 2018 (i.e., resulting in no statistical significance in the proportions test) but either spiked or plummeted in the years between. However, we examined each item to verify whether this scenario existed, and we could not find any item that had a significant rise or fall of the trend between 2014 and 2018 with 2014 and 2018 having approximately the same value. There is another possible scenario in which the proportion test may indicate a positive increase, but the overall trend is declining in the last few years. For example, one item could start at 12% in 2014, spike to 20% in 2015, then decline steadily over the next 3 years to 15% by 2018. Obviously, this is a declining trend and would be a fading trend in the analytics space, but our proportion test would show a significant increase between 2014 and 2018. We checked the entire dataset and could not find an example of this trend. Therefore, we are confident that the proportion test adequately answers our research questions.

Our third limitation is that we only examined entry-level positions and only general domain skills and software skills. A comprehensive study would have examined all levels and included soft skills. We decided not to include these analyses in this research due to sample size limitations. These analyses would be included in future research.

Our last limitation is that we examined job postings written by employers themselves. Each company may have a different idea of what a skillset is for their employees. Therefore, there could be variance in vague general domain skills like general statistics. However, this limitation is also a contribution of our research since we summarized over 9,000 job postings over 5 years. Our summarized results show that general domain skills like general statistics are still widely used in job postings.

6. CONCLUSION

In summary, this research examined job postings from 2014 to 2018 for entry-level data analytics jobs from Indeed.com. Using a custom data dictionary built from previous literature and empirical data, we employed a text mining approach to identify word frequencies in the job postings. Using a difference of proportions, we identified general domain skills and software skills that trended over time. General analytics, general statistics, modeling, and data management all appear in at least 20% of the job postings in our sample, with general analytics appearing in almost 70% of job postings. We find that Python, Tableau, and R software skills are in high demand, and Microsoft Access, Cognos, and SAP are in slow decline. We also analyzed job postings by state and education level. We find that at least a bachelor's degree is required in 70% of the job postings in our sample. Using the results of the study, universities can make better-informed curriculum decisions, and instructors can decide what skills to teach based on industry needs. Our custom text mining dictionary can be added to the growing literature and assist other researchers in this space. We also identified limitations to this research and ideas for future work.

7. ACKNOWLEDGEMENTS

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8. REFERENCES

Aasheim, C., Li, L., & Williams, S. (2009). Knowledge and Skill Requirements for Information Technology Graduates: A Comparison of Industry and Academia. *Journal of Information Systems Education,* 20(3), 349-356.

Aasheim, C., Shropshire, J., Li, L., & Kadlec, C. (2012). Knowledge and Skill Requirements for Entry-Level IT Workers: A Longitudinal Study. *Journal of Information Systems Education,* 23(2), 193.

Aasheim, C., Williams, S., & Butler, E. S. (2009). Knowledge and Skill Requirements for IT Graduates: A Survey of IT Workers and Managers. *Journal of Computer Information Systems,* 42, 690-699.

Aasheim, C., Williams, S., Rutner, P., & Gardiner, A. (2015). Data Analytics Vs. Data Science: A Study of Similarities and Differences in Undergraduate Programs Based on Course Descriptions. *Journal of Information Systems Education,* 26(2), 103-115.

Aken, A., Litecky, C., Ahmad, A., & Nelson, J. (2010). Mining for Computing Jobs. *IEEE Software,* 27(1), 78-85.

Batikas, M., Claussen, J., & Peukert, C. (2018). Follow the Money: Online Piracy and Self-Regulation in the Advertising Industry (SSRN Scholarly Paper ID 3140358). *Social Science Research Network.* https://papers.ssrn.com/abstract=3140358.

Bila, A. (2018). 7 Top Tech Skills In High Demand For 2019, LinkedIn. Retrieved September 9, 2019, from https://www.linkedin.com/pulse/7-top-tech-skills-high-demand-2019-anna-bila.

Bloom, B. S. (1956). *Taxonomy of Educational Objectives: Handbook 1: Cognitive Domain*. New York: David McKay.

Bowers, J. W. & Courtright, J. A. (1984). *Communication Research Methods.* Glenview, Illinois: Scott, Foresman.

Bowne-Anderson, H. (2018). What Data Scientists Really Do, According to 35 Data Scientists. *Harvard Business Review.* Retrieved September 1, 2019, from https://hbr.org/2018/08/what-data-scientists-really-do-according-to-35-data-scientists.

Burkholder L. (1992). *Philosophy and the Computer*. Boulder, Colorado: Westview Press.

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly,* 36(4), 1165-1188.

Church, K. W. (1988). A Stochastic Parts Program and Noun Phrase Parser for Unrestricted Text. *Second Conference on Applied Natural Language Processing*, 136-143.

Cafarella, M., Halevy, A., Lee, H., Madhavan, J., Yu, C., Wang, D. Z., & Wu, E. (2018). Ten Years of Webtables. *Proceedings of the VLDB Endowment*, 11(12), 2140-2149.

Columbus, L. (2017). IBM Predicts Demand for Data Scientists Will Soar 28% By 2020. *Forbes*. Retrieved September 19, 2019, from https://www.forbes.com/sites/louiscolumbus/2017/05/13/ibm-predicts-demand-for-data-scientists-will-soar-28-by-2020/#670c4c217e3b.

Davenport, T. H., Barth, P., & Bean, R. (2012). How Big Data Is Different. *MIT Sloan Management Review*, 54(1).

Davenport, T. H. & Patil, D. (2012). Data Scientist. *Harvard Business Review,* 90(5), 70-76.

Deng, X. N., Li, Y., & Galliers, R. D. (2016). Business Analytics Education: A Latent Semantic Analysis of Skills, Knowledge and Abilities Required for Business Versus Non-Business Graduates. *Proceedings from Thirty Seventh International Conference on Information Systems*, Dublin.

Gallivan, M. J., Truex III, D. P., & Kvasny, L. (2004). Changing Patterns in IT Skill Sets 1988-2003: A Content Analysis of Classified Advertising. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, 35(3), 64-87.

Gardiner, A., Aasheim, C., Rutner, P., & Williams, S. (2018). Skill Requirements in Big Data: A Content Analysis of Job Advertisements. *Journal of Computer Information Systems, 58*(4), 374-384.

Gupta, B., Goul, M., & Dinter, B. (2015). Business Intelligence and Big Data in Higher Education: Status of a Multi-Year Model Curriculum Development Effort for Business School Undergraduates, MS Graduates, and MBAs. *Communications of the Association for Information Systems,* 36(23), 449-476.

Holsapple, C., Lee-Post, A., & Pakath, R. (2014). A Unified Foundation for Business Analytics. *Decision Support Systems,* 64, 130-141.

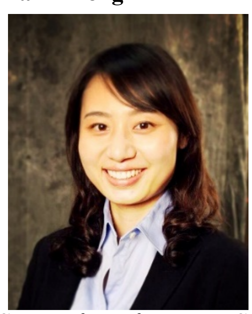
Jurafsky, D. & Martin, J. H. (2008). Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition. *Prentice Hall Series in Artificial Intelligence*, 1-1024.

Key Industries. (n.d.). Virginia Economic Development Partnership, Retrieved September 1, 2019, from www.vedp.org/key-industries.

Khambhammettu, P. (2005). Mann-Kendall Analysis, HydroGeoLogic Inc. *OU-1 Annual Groundwater Monitoring Report–Former Fort Ord, California*.

Landis, J. R. and Koch, G. G. (1977). The Measurement of Observer Agreement for Categorical Data. Biometrics, 33(1), 159-174.
Lauby S. (2013). The Difference between Knowledge, Skills and Abilities. *HR Bartender* Retrieved from https://www.hrbartender.com/2013/recruiting/the-difference-between-knowledge-skills-and-abilities/.
Lewis-Beck, M. S. (1995). *Data Analysis: An Introduction*, Sage Publications, Inc.
Liberatore, M. & Luo, W. (2013). ASP, The Art and Science of Practice: A Comparison of Technical and Soft Skill Requirements for Analytics and OR Professionals. *Interfaces*, 43(2), 194-197.
Loukides, M. (2011). *What is Data Science? O'Reilly Media, Inc.* Retrieved August 22, 2019, from https://www.oreilly.com/radar/what-is-data-science/.
Luo, W. (2016). Responsibility and Skills Requirements for Entry Level Analytics Professionals. *Journal of Organizational and End User Computing,* 28(4), 1-14.
Lyon, L., Mattern, E., Acker, A., & Langmead, A. (2015). Applying Translational Principles to Data Science Curriculum Development. *iPRES 2015*.
Microsoft Community Support Pages. (2017). "Decline in use of Access Database?" Retrieved April 29, 2019, from https://answers.microsoft.com/en-us/msoffice/forum/all/decline-in-use-of-access-database/3407c710-7b98-4abe-835c-cb7c8b533641.
Miller, S. & Hughes, D. (2017). The Quant Crunch: How the Demand for Data Science Skills is Disrupting the Job Market. Retrieved from https://www.bhef.com/publications/quant-crunch-how-demand-data-science-skills-disrupting-job-market.
Mills, R. J., Chudoba, K. M., & Olsen, D. H. (2016). IS Programs Responding to Industry Demands for Data Scientists: A Comparison Between 2011-2016. *Journal of Information Systems Education,* 27(2), 131.
Moore, E. (2018). 9 Perfect Jobs for Career Changers. *Glassdoor*. Retrieved July 19, 2019, from https://www.glassdoor.com/blog/jobs-for-career-changers/.
Mosbrucker, K. (2018). Microsoft Plans for More Area Data Centers Worth $62M, *Bizjournals.com*, Retrieved July 19, 2019, from www.bizjournals.com/sanantonio/news/2018/09/07/microsoft-plans-for-more-area-data-centers-worth.html.
Mudambi, S. M., & Schuff, D. (2010). What Makes A Helpful Review? A Study of Customer Reviews on Amazon.com. *MIS Quarterly,* 34(1), 185-200.
NAICS Association. (2019). Retrieved August 8, 2019, from https://www.naics.com/business-lists/counts-by-state/.
Pal, K. (2016). Why the World is Moving toward NoSQL Databases?" *Techopodia*. Retrieved June 7, 2016, from https://www.techopedia.com/2/32000/trends/big-data/why-the-world-is-moving-toward-nosql-databases.
Power, D. J. (2007). A Brief History of Decision Support Systems. Retrieved from DSSResources.com.
PWC. (2017). Investing in America's Data Science and Analytics Talent. Retrieved from http://pwc.com/us/dsa-skills.
Schlee, R. & Harich, K. (2010). Knowledge and Skill Requirements for Marketing Jobs in the 21st Century. *Journal of Marketing Education*, 32(3), 341-352.
Scorsone, G. (2018). 5 Hot and High-Paying Tech Skills for 2018. Retrieved July 19, 2019, from https://www.idginsiderpro.com/article/3269251/5-hot-and-high-paying-tech-skills-for-2018.html.
Silva, Y. N., Dietrich, S. W., Reed, J. M., & Tsosie, L. M. (2014). Integrating Big Data into the Computing Curricula. *Proceedings of the 45th ACM Technical Symposium on Computer Science Education*.
Sodhi, M. & Son, B. G. (2009). Content Analysis of OR Job Advertisements to Infer Required Skills. *Journal of the Operational Research Society*, 61(9), 1315-1327.
Toutanova, K. & Manning, C. D. (2000). Enriching the Knowledge Sources Used in a Maximum Entropy Part-Of-Speech Tagger. *Proceedings of the 2000 Joint SIGDAT Conference on Empirical Methods in Natural Language Processing and Very Large Corpora: Held in Conjunction with the 38th Annual Meeting of the Association for Computational Linguistics*, 13, 63-70.
Turel, O. & Kapoor, B. (2016). A Business Analytics Maturity Perspective on The Gap Between Business Schools and Presumed Industry Needs. *Communications of the Association for Information Systems*, 39(6), 96-109.
Voutilainen, A. (2003). Part-Of-Speech Tagging. *The Oxford Handbook of Computational Linguistics*. 219-232.
Wang, T., Kannan, K. N., & Ulmer, J. R. (2013). The Association between the Disclosure and The Realization of Information Security Risk Factors. *Information Systems Research,* 24(2), 201-218.

AUTHOR BIOGRAPHIES



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APPENDIX A. Final Dictionary (Categories, Subcategories, and Keywords)

<table>
<tr><th colspan="3">1.Technical Skills</th></tr>
<tr>
<td>1.1 General Analytical
Analysis
Analysis and design
Analysis and reporting
Analysis skills
Analysis support
Analysis techniques
Analysis to support
Analysis tools
Analytic support
Analytical abilities
Analytical methods
Analytical projects
Analytical results
Analytical support
Analytical techniques
Analytical tools
Analyzing information
Quantitative analysis
Quantitative and qualitative

1.2 General Statistics
anova
Advanced statistics
Data modeling
Linear and logistic
Linear models
Predictive models
r-square
Regression
Statistical analyses
Statistical analysis
Statistical data analysis
Statistical methods
Statistical modeling
Statistical models
Statistical process
Statistical reports
Statistical techniques
Statistical tests
Statistics
Summarizing data</td>
<td>1.3 Modeling
Algorithm
Algorithm design
Algorithm development
Algorithms
Algorithms and applications
Algorithms and formulations
Algorithms in solving real
Algorithms to match online
AMPL
Combinatorial optimization
Constraint based
Constraint programming
Cplex
Decision analysis
Decision making
Decision problems
Decision science
Decision sciences
Decision support
Decision support analysis
Decision support applications
Decision support functions
Decision support models
Decision support research
Decision support research analyst
Decision support software
Decision support systems
Decision support tools
Decision tools
Decision trees
Forecasting
Integer
Linear programming
Mathematical modeling
Mathematical models
Mathematical programming
MATLAB
Nonlinear
Non-linear
Optimization
Quadratic
Stochastic optimization</td>
<td>1.4 Model development
Model development
Model formulation
Modeling
Network modeling
Simulate
Simulation
Simulations

1.5 Data Management
Data analysis
Data set
Data collection
Data gathering
Data integrity
Data mining
Database management
Datamart
Dataset
ERD
etl
Large data
Relational databases
Software applications</td>
</tr>
</table>

2. Software Package Skills		
2.1 Personal Productivity Computer skills Macros Microsoft Office Microsoft suite Microsoft Word MS Office MS Word o365 Power Point PowerPoint Spreadsheet Spreadsheets Word processing *2.2 Business Intelligence* Cognos fixml d3 pentaho powerbi tableau	*2.3 Database Systems* Access and And access cassandra DB2 dbms Hbase Microsoft Access mongodb MS Access Mysql Nosql Oracle SQL Server *SQL* Teradata tsql *XML* xsd xsl *2.4 Stats Packages* r SAS SPSS STATA	*2.5 Programming Language* C C++ html Linux Pearl Perl pig Python ruby VBA Visual Basic *2.6 Enterprise System* Azure Google Analytics Hadoop Hive Salesforce SAP Watson

3. Academic Degree		
3.1 Bachelor's Accredited college BA Bachelor of business administration Bachelor of science Bachelor's Bachelor's degree BS College or university	*3.2 Master's* Advanced degree Doctorate Graduate degree Master's Master's degree MS degree	*3.3 Ph.D.* Master of business administration MBA MBA degree Ph PhD PhD degree

APPENDIX B. Evolution of Software Skills for Data Analysts

Categories and Sub-Categories	**2014**	**2015**	**2016**	**2017**	**2018**
Personal Productivity	30.70%	29.70%	32.60%	32.10%	28.60%
Microsoft Office	18.40%	16.30%	20.60%	18.50%	17.20%
MS Power Point	12.10%	13.70%	13.70%	14.20%	13.90%
MS Excel	4.20%	3.90%	3.70%	5.80%	4.20%
MS Word	3.50%	4.70%	4.30%	3.80%	3.30%
Macros	1.70%	2.40%	1.50%	1.90%	1.50%
o365	0.00%	0.00%	0.20%	0.10%	0.00%
Database System	48.00%	48.80%	52.40%	58.10%	58.90%***
SQL Server	10.40%	12.10%	13.40%	15.20%	17.80%***
Oracle	15.00%	14.00%	13.40%	14.40%	15.50%
Microsoft Access	13.60%	11.60%	11.30%	11.60%	10.40%**
Teradata	2.30%	2.50%	2.50%	2.80%	3.10%
MySQL	1.50%	1.80%	3.00%	2.50%	2.10%
XML	2.70%	2.80%	3.00%	3.00%	2.00%
NoSQL	0.70%	1.00%	1.60%	1.50%	1.60%**
DB2	2.00%	2.00%	1.90%	1.60%	1.60%
DBMS	0.30%	0.60%	0.60%	0.90%	0.90%*
Hbase	0.30%	0.20%	0.30%	0.40%	0.60%
MongoDB	0.20%	0.40%	0.80%	0.40%	0.30%
tsql	0.50%	0.40%	0.60%	0.80%	0.20%
Cassandra	0.30%	0.20%	0.20%	0.30%	0.20%
xsl	0.00%	0.30%	0.00%	0.10%	0.00%
xsd	0.00%	0.20%	0.20%	0.00%	0.00%
Business Intelligence	11.30%	12.60%	17.60%	21.80%	23.20%***
Tableau	5.30%	8.30%	13.20%	18.20%	18.90%***
Cognos	7.50%	5.30%	5.30%	5.80%	6.00%*
PowerBI	0.10%	0.10%	1.00%	1.60%	1.90%***
Pentaho	0.40%	0.80%	0.60%	0.60%	0.30%

JavaScript D3	0.20%	0.00%	0.50%	0.40%	0.20%
fixml	0.00%	0.20%	0.20%	0.00%	0.00%
<u>Statistical Package</u>	10.10%	9.50%	12.40%	15.40%	16.10%***
SAS	6.60%	6.60%	8.00%	8.80%	9.70%***
SPSS	1.60%	1.90%	2.40%	3.70%	2.50%*
R	4.50%	4.40%	7.00%	9.60%	11.80%***
STATA	0.60%	0.40%	0.40%	1.10%	0.50%
<u>Programming Language</u>	16.00%	16.40%	20.20%	21.90%	22.50%***
Python	2.30%	3.30%	6.60%	9.10%	10.70%***
C	9.60%	7.90%	8.60%	9.90%	9.60%
HTML	2.80%	3.00%	3.90%	2.50%	2.70%
VBA	1.90%	2.60%	2.90%	2.60%	2.50%
Linux	1.90%	1.90%	2.50%	2.00%	1.70%
Visual Basic	1.40%	1.30%	1.40%	1.60%	1.20%
Pig	0.30%	0.50%	0.70%	0.60%	1.00%**
Perl	1.00%	0.90%	0.80%	1.60%	0.90%
Ruby	0.50%	0.30%	0.90%	1.20%	0.30%
C++	0.00%	0.00%	0.00%	0.00%	0.00%
Pearl	0.00%	0.20%	0.20%	0.10%	0.00%
<u>Enterprise System</u>	16.00%	15.80%	16.20%	18.50%	20.30%***
SAP	10.40%	9.00%	8.00%	8.40%	8.30%*
Hadoop	2.00%	2.40%	4.00%	4.50%	5.10%***
Salesforce	3.40%	4.50%	2.80%	4.50%	4.90%*
Azure	0.20%	0.00%	0.80%	1.30%	3.60%***
Hive	0.70%	1.10%	1.80%	1.80%	2.10%***
Google Analytics	0.50%	0.50%	1.50%	1.00%	1.20%*
Watson	0.40%	0.20%	0.10%	0.30%	0.20%

*p < 0.05, **p < 0.01, ***p < 0.001
Categories are underlined; Subcategories are indented.
Bold (*italicized*) text indicates a positive (negative) trend between 2014 and 2018.

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